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The importance of ergonomic design in product innovation. Lessons from the development of the portable computer

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Abstract

The article addresses the role of ergonomic design in product innovation. Designers meet users' needs by developing solutions to complex trade-offs—reverse salients—between a product's characteristics. The fundamental ergonomic design challenge in portable computers concerns the reverse salient between two ergonomic factors: screen size and weight. It is easier to view information on larger screens, but portability is negatively affected by the weight of larger batteries required to power larger screens. This ergonomic reverse salient shaped the innovation trajectory of the portable computer, from the selection of the clamshell portable over alterative design configurations, to the search for more efficient batteries and new types of screens. Based on hedonic price analysis on data of ergonomic and technological characteristics, we show that (i) screen size and weight are key components in hedonic price functions, (ii) the interaction between screen size and weight is distinct from interactions between other, technological, characteristics that affect computing power, and (iii) positive prices are paid for the product solutions to the ergonomic reverse salient.

JEL classification: O32, L63, C12

1. Introduction

This article contributes to a growing body of research on design and innovation by addressing the role of design ergonomics in product development. Prior studies have highlighted the contributions of design and aesthetics to product development (Bloch, 1995; Postrel, 2003, Eisenman, 2013), the designer as technology interpreter and practical translator (Lawson, 2006), and the integration of design, engineering, and marketing functions in the new product development process (Moenaert and Souder, 1990; Perks *et al.*, 2005). In addition, some recent contributions have focused on design as a driver for innovation (Verganti, 2009), "design thinking" as a means of structuring strategic product development (Brown, 2008), and the role of design in articulating creativity and innovation (Cox, 2005). While these contributions foreground key aspects of the design–innovation relationship, their focus falls squarely on issues of technology, aesthetics, and the management of the product development process.

In contrast to the fields listed above, the role of design ergonomics as a critical input to product innovation has remained an under-researched topic. Ergonomics is concerned with the ways in which a physical artifact interacts with the human body, and with the environment in which the artifact/human is expected to move and operate. It involves "design for effective use," which explicitly takes account of the user's physical and psychological capabilities and limitations (Boff, 2006; Salvendy, 2012). To assess the fit between the user and the artifact, i.e., the latter's "human compatibility" (Karwowski, 2005), the designer must analyze the physical attributes of the typical user, the activity being performed, and the demands placed on the user by the product during the activity. Of particular importance, here are the size, shape, weight, and configuration of the product, and how appropriate these are for the task.

Ergonomics is central to the effective design and application of a wide range of products, for example, medical devices that aid hearing or mobility, office equipment that minimizes repetitive strain, or kitchen utensils that provide safety and comfort in extended use. In portable devices, such as portable computers, designers face the challenge of addressing a "reverse salient" (Hughes, 1983, 1987) that exists between two ergonomic features: here, screen size and overall weight. Larger screens are ergonomically beneficial because viewing is easier for the user. However, larger screens require bulkier and heavier batteries, and these adversely affect the portability of this electronic device. Hence, the ergonomic penalty of larger screens is the increased weight of a device that the user is likely to need to transport, and to place in their lap when in use.

The problem of weight in portable computers is an ergonomic reverse salient that impeded the overall rate of progress of the whole product, since critical components such as screen size, could not be permitted to increase total unit weight beyond reasonable parameters. The ways in which designers have sought to address this ergonomic reverse salient have shaped significantly the innovation trajectory of the portable computer. Impacts include the development of the clamshell design configuration, new types of screen technologies, the development of ergonomic standards for human–screen interaction, and the search for more efficient battery types.

In addition to meeting a set of ergonomic requirements through the product's design, designers are required to develop a set of measurable indicators that clearly convey information with respect to the product's ergonomic performance to the consumer. These indicators are strategically important to firms as a means of differentiating the quality of their product offerings vis-à-vis rival products. In the Lancaster tradition of product innovation (Lancaster, 1966, 1971), these measurable features are known as "product characteristics." The information that is reported by firms in their product specifications is an important input to the reviews conducted by specialist consumer magazines, and is used by consumers in their purchasing decisions. Seminal research by Alba and Hutchinson (1987, 2000) highlights the importance of information on ergonomic and technical performance in consumers' decision-making. Knowledgeable consumers place greater weight on product attribute information than on advertising exposure or direct interactions with salespersons.

The role of designers is to meet the expressed and latent needs of users through product design, given prevailing and anticipated production capabilities, and the costs of realizing these product characteristics. Consumers are the ultimate arbiters of whether designers develop effective solutions to reverse salients. Hence, we use information collected on the ergonomic and technological product characteristics[1] of laptop computers, available to consumers when making their purchasing decisions, to empirically test two research hypotheses. The first hypothesis examines whether a positive price is paid for designers' solutions to the screen-weight ergonomic reverse salient. As noted above, larger-sized screens are easier to read but carry the penalty of larger and heavier batteries required to run them: this is a penalty that impacts negatively on device portability. The second hypothesis examines whether a positive price is paid for solutions to the technology reverse salient associated with computing power. These hypotheses are tested by estimating a set of hedonic price models. Our findings indicate that positive prices are paid for products that address the ergonomic reverse salient as well as the technological reverse salient. This highlights the need for a deeper understanding, and analysis, of the contributions of ergonomic design to product innovation. As Stoneman (2010) has argued, studies which omit these contributions—focusing solely on improvements in technologically driven performance—significantly under-report innovation.

1 Note that both ergonomic and technological characteristics are examples of "service characteristics" in the sense of Saviotti of Metcalfe (1984), that is, characteristics that are explicitly valued by users.

2. Reverse salients and product design

The "reverse salient" concept entered innovation and technological development discourses in the early part of the 1980s, most notably via the contributions of Hughes (1983, 1987). It derives in its current application from the study of technologies and complex products as "systems," i.e., those approaches that view technological products as interdependent systems and subsystems of components (Henderson and Clark, 1990; Murmann and Frenken, 2006). In its most simple form, the notion of reverse salience is applied to reference those components in a complex and coevolutionary nexus in which development is retarded. As a consequence of their limitations, such components are likely to impede the overall rate of progress of a product or system as a whole.

The concept of reverse salience relates closely to that of "bottlenecks" or "technological imbalances" (Rosenberg, 1969; Dedehayir, 2009) in the coevolution of interlinked elements within a product or system. Where optimal progress in performance requires that all interdependent components or subsystems develop with orchestrated continuity, the failure to maintain pace of one component—the appearance of a reverse salient—will imply disruption to the collective system's "advancing performance frontier" (Dedehayir, 2009: 576). Clearly, where possible, the emergence of reverse salients is to be avoided: however, where the latter are encountered, interventions are required to ensure rapid correction (Hughes, 1987). Here, we see the reverse salient as a "focusing device" (Rosenberg, 1969), that is, a problem around which system actors (technologists, engineers, designers, managers, marketers, etc.) will agglomerate in the effort to derive appropriate solutions and thus reestablish developmental equilibrium.

The role of designers in tackling reverse salients is central: designers address reverse salients by developing product designs that configure the user in specific ways, and different designers may come up with very different design solutions for their intended consumers (Woolgar, 1991, 1994). The three core areas of competence in which designers contribute to the product development process—ergonomic, aesthetic, and technological—are founded on two transversal capabilities (Miles and Green, 2008). First, an ability to recognize and respond to expressed and latent needs of potential users. Second, an ability to derive solutions to the complex problems that emerge frequently in the process of envisioning and creating new industrial and consumer products. Indeed, problem-solving capability lies at the core of product design endeavor (Suh, 2001; Lawson, 2006), and experienced designers are arguably well-equipped to manage emergent difficulties in the coevolving nexus of technological, aesthetic, and ergonomic factors that characterize the development of complex contemporary products.

While several models of the design-led problem-solving process appear in the design literature (Cross, 2001), most approaches are premised on a sequential (feedback looped) flow that commences with problem framing (or definition), and proceeds in various steps through research and exploration, idea generation, experimentation with alternative solutions, idea synthesis and selection, and on to prototyping and implementation. Frequently characterized as a process that commences with "divergent" and concludes with "convergent" thinking (i.e., one that moves from the identification of many solutions to the selection of an optimal fix), the resolution of reverse salients—whether these arise within or between ergonomic, aesthetic, or technological factors in new product development—is an activity with which the design profession is well-acquainted, and one that is embedded in training and reinforced by practice (Schon, 1983; Hill, 1998; Cross, 2001).

Two important reverse salients are evident in the developmental trajectory of portable computing. One concerns "processing power" and is common to both portable and desktop computers. Computing power is a complex phenomenon that governs both computer speed and software stability. The reverse salient that arises in relation to computing power centers on the balance required in the development of microprocessors and disk drives (Baldwin and Clark, 2000). Computing power depends on interactions between the random access memory (RAM) of a microprocessor and disk drive storage. A computer program requires contiguous working memory. In practice, this is physically fragmented on RAM and may overflow on to disk storage. Memory is managed by "virtual memory," which frees up RAM by identifying areas that have not been used recently and copies them on to the hard disk. The area of the hard disk that stores the RAM image is called a page file. A balanced design requires developments in RAM that are matched by developments in disk drive capacity. The advantage of hard disk memory is that it is cheap (compared to RAM). However, the read/write speed of a hard drive is much slower than RAM and is not as effective in accessing fragments of data. A design which is overly dependent on virtual memory suffers in terms of performance. In the worst case, "thrashing" occurs, and the computer grinds to a halt as the operating system constantly swaps information between RAM and hard disk memory.

The second reverse salient is ergonomic in nature, and concerns a fundamental trade-off between usability and portability. Larger screens make it easier for users to view information and to work with data entry and data output. However, the operation of such screens in typical use-time scenarios requires larger, heavier batteries. The increase in total weight renders the product less portable, as it is more onerous to carry and less comfortable when placed on one's lap. As we shall see in the next section of the article, the ergonomic screen size–weight reverse salient has been a key driver of innovation in portable computers.

In contrast to the relationship between prices and computing power, portability and the reverse salient between screen size and weight have been downplayed or sometimes ignored in previous studies. This is even the case in the few examples of studies of portable computer pricing (Nelson *et al.*, 1994; Berndt *et al.*, 1995; Baker, 1997; Berndt and Rappaport, 2001; Chwelos, 2003). To the extent that these studies have examined portability as a characteristic, it has been operationalized typically solely in terms of weight or volume.

3. Screen size–weight reverse salient in portable computers

Compared to contemporary personal computers (PCs), early portables provided significantly reduced processing power: a key advantage, however, was their mobility. For the first time, salespeople could sit with clients to discuss, display, and configure product options, and then produce instant quotes using powerful spreadsheet software. This gave portable users an edge over competitors who needed to refer information back to local offices to have quotes drawn up and posted out. Salespeople were also able to complete standardized electronic orders remotely, and collect or log other information that could be used to update company databases on their return to the office. For senior executives, portables enabled remote working and work while travelling. Thus, it became possible to develop presentations and budget sheets on the move, and to refresh and update information and content between meetings (Gatignon and Robertson, 1989). For both sales and executive users, larger screen sizes were highly important, as these permitted the presentation of material to small groups around a table.

The first commercially successful portable computer was a "portable box" design, the Osborne I, released in April 1981.[2] Portable box computers are often referred to as a "luggables" due to their relatively large size—about the size of a small suitcase—and weight (e.g., the Osborne I weighed almost 24 lbs). The unit opened on one side to reveal a small, 5" monochrome cathode ray tube (CRT) display and a fold-down keyboard. CRTs were, at that time, a well-established screen type, having had a long history of use and incremental development in televisions. The big disadvantage of CRTs was weight, even for modestly sized CRT units. Given the physical size and weight of the portable box design, it was intended that operators should sit at a desk, thus limiting the use of portable boxes to an office or workplace environment. The sheer mass of boxes also limited general mobility for many users.

In the rival "clamshell" design, the user was configured differently. The clamshell is a more compact and lighter weight design comprising a large flat screen set into a unit that is intended to be balanced on the user's lap leaving both hands free to type, hence the term "laptop computer" (Safire, 1988).

The "clamshell" concept was initially created and developed by Bill Moggridge, a leading British industrial designer, in association with GRiD. The design is a "form factor"—it comprises two sections that fold via a hinge. The components are kept inside the clamshell, and the latter is opened up when in use. The design was patented (US Patents D280,511 and 4,571,456) for the GRiD Compass portable computer, which was launched in April 1982. The GRiD Compass sported a large, flat panel (monochrome) electroluminescent display screen. Processing hardware (Intel processor, RAM, and data storage memory) and the battery were housed in a rectangular magnesium case, designed to ensure high levels of component protection and an efficient heat dissipation mechanism. The Compass weighed just 11 lbs (Wilson, 2006).

The ergonomic attractiveness of the clamshell vis-a-vis the portable box design was a key selling point for the early adopters or "lead users" (von Hippel, 1986) purchasing portables during the early 1980s. As noted, early portables were expensive business machines that were targeted at field salespeople and senior executives. When launched, the Osborne I had a price tag of US$1795.00, and the GRiD Compass retailed at more than US$8000.00.

The clamshell quickly became the dominant industry design. Still, the ergonomic reverse salient between screen size and weight persisted as a key innovation driver. Rival product designers engaged in the development of machines with larger, higher quality flat screens, and in experimentation with new battery types.

2 The first portable computer predates the release of the first IBM PC (5150), which was launched in August 1981 in the United States.

Portable designers explored the possibilities of larger screens using liquid crystal displays (LCDs).[3] The Toshiba T1100 (released in April 1985) was the first clamshell to use a backlit LCD. These screens are particularly suited to the clamshell design: they provide better resolution and luminosity than electroluminescent counterparts, and their lightness and thinness are particularly suited to use in the clamshell lid. Further, the low electrical power consumption of LCDs places less demand on batteries. Indeed, it was the commercial success of the clamshell portable that bootstrapped the development of LCDs during the 1990s (Lien *et al.*, 2001).

Improved visibility also required a scientific understanding of screen visualization and the development of a set of standards to underpin the work of specialist ergonomic designers. Human–screen interaction standards were developed during the late 1980s and early 1990s and were quickly adopted by portable computer firms. These cover the recommended reading distance of a display (Boff and Lincoln, 1999), the useful field of view (Ware, 2004), luminescence (Shneiderman, 1992), font size and font type (Sanders and McCormick, 1993; Mayhew, 1999), and color contrast (Ware, 2004). With these standards in place, the remaining variable governing user's ease of reading is total screen area (height $\times$ width).

To address the issue of progressive increase in weight, and to safely power larger LCD screens (overstressing a battery can result in catastrophic meltdown) designers experimented with new, more powerful nickel metal hydride (NiMH) and lithium-ion (Li-ion) battery types. In the late 1980s, designers switched from nickel–cadmium batteries to NiMH batteries. NiMH has a 30%–40% higher capacity over nickel–cadmium, is less prone to battery memory loss, offers simple storage and transportation, and is more environmentally friendly (Linden and Reddy, 2001). In the early 1990s, NiMH was in turn replaced by Li-ion batteries that have a longer service life and a higher electrochemical potential: even today these cells possess the largest density for weight of all currently available options (van Schalwijk and Scrosati, 2002). As with screen displays, the scale and economic significance of the portable computer sector was such that it induced key innovations in the related battery sector.

4. Statistical methods

We have chosen to test our hypotheses using hedonic regression analysis on published data of laptop prices and product characteristics during a particular historical period: that of 1993–1996. The reasons for this are as follows. One of the most important problems facing those estimating product features, regardless of statistical method, is misspecification due to omitted variables. During the period 1993–1996, portables were stand-alone business machines that contained relatively few well-defined hardware features, compared to subsequent years. After this period there was a proliferation of hardware features. If one were to estimate characteristics prices today, for example, omitted variable problems due to multiple hardware features would be far greater.[4]

There are sources of omitted variable bias that would adversely affect a study of current laptop machines but which are avoided by examining this historical period. First, the chosen period predates the commercialization and widespread use of the Internet and the worldwide Web. It was also an era before software plug-ins and apps. Another potential source of omitted variable bias is software–hardware bundling. Rival hardware manufacturers may include alternative types of software within their offer prices (Triplett, 2006). In the period 1993–1996, there was a high degree of standardization around a limited number of business software packages—certainly by comparison with today. The package software market at this time was dominated by Lotus Symphony and Excel (spreadsheets), WordPerfect and Word (word processing packages), and PowerPoint. We note that all of the laptops listed in our data set used Microsoft's Windows 3.0 operating system.

3 An organic liquid is the active ingredient in an LCD panel; argon or neon gas in a gas plasma screen; a metal film in an electroluminescent screen.

4 An alternative approach to identifying preferences is discrete choice analysis (also known as conjoint analysis). Here customers are asked to state their willingness to pay for multiple product characteristics. This has a number of well-known limitations. These include limited levels of characteristics which respondents are asked to consider (in the limit these are binary options), and the information and computational demands placed on respondents in consistently scoring or ranking more than a few characteristics. Problems of omitted variable bias arise. Over the past decade, the focus has been on developing computer-based techniques that guide respondents through a limited subset of product characteristics. This does not resolve the issue of omitted variable bias, per se, and there is, as yet, no consensus on these subset approaches (Hauser and Rao, 2004; Hainmueller et al., 2014).

A further advantage in using this period is that (the limited) prior research on laptop computers by Baker (1997) and Chwelos (2003) also consider this period. It provides a useful basis of comparison. Also, these papers previously addressed issues, such as the relationship between product characteristic variables (e.g., megahertz) and benchmark computing system performance. Chwelos (2003) found, during the era that we are considering, that the price index differs trivially between benchmark performance measures and a set of product characteristics. Triplett (2005) observes that one reason for this result is that Chwelos' product characteristic specification was unusually rich, including microprocessor clock speed, cache memory (RAM), and hard disk capacity. The same result may not hold in simpler hedonic price regression models that include fewer product characteristics.

Another advantage in studying the 1993–1996 period is that there was a clear set of lead users for this product. Businesses purchased these machines for use by salespeople and senior managers. The ergonomic reverse salient was an important consideration for these particular users. Larger screens were valued by salespeople in the field because they were able to demonstrate to clients alternative options and plans. Larger screens were also useful for mobile senior managers when delivering presentations to clients and other business leaders. Minimizing weight was important to both groups given the requirement for ease of portability while on the road.

Finally, a large number of competing US, European, and Asian manufacturers were producing and selling products internationally during this era. This provides a large number of product observations on a relatively small number of key ergonomic and non-ergonomic product characteristics.

Ideally, one would like to have data on sales of each individual portable as well as data on prices and product features. In reality, this is rarely, if ever, available to the analyst (Bhaskarabhatla and Klepper, 2014). We have collected historical data from contemporary US Census Bureau's Current Industrial Report series, "Computers and Office and Accounting Machines" (annually): domestic shipments, imports, and exports. Using these data, we report in Figure 1 total sales of all portables sold in the United States during this period. What these data show is that the market for portable computers only started to develop in the mid-1990s, which corresponds to our period of analysis. This strengthen our belief that the period chosen is the relevant period during which fundamental design issues, possibly associated with reverse salient, were being addressed and solved.

We apply hedonic regression methods to this data set to estimate whether positive prices are paid for product solutions to the ergonomic and technological reverse salients. The hedonic regression method recognizes that heterogeneous goods can be described by their attributes or "characteristics." This conceptualization follows a long tradition of work in marketing, decision science, and economics (Court, 1939; Stone, 1956; Griliches, 1957, 1971; Lancaster, 1966, 1971; Green and Wind, 1973; Rosen, 1974).

The hedonic price model posits that a product comprises a set of inherent attributes, or "characteristics" that are attractive to consumers. Hedonic functions are envelopes that involve both supply and demand factors (Rosen, 1974). Estimated coefficients are estimates of the prices of individual product characteristics, otherwise known as shadow prices, which depend on both users' valuations and producers' costs (Triplett, 2006: 200).

It is important to note that this is an equilibrium model. The prices offered by firms on the market reflect the underlying marginal costs of producing a set of K characteristics. Ceteris paribus, marginal costs are higher for a firm

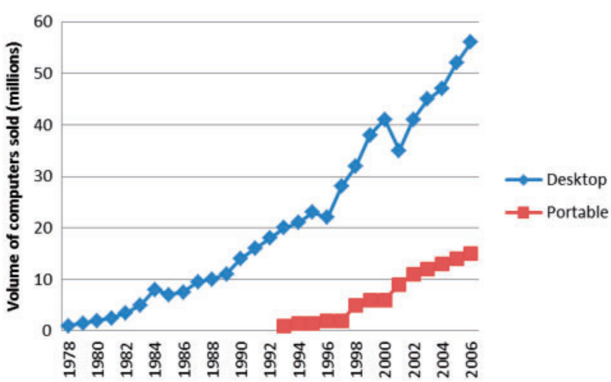

Figure 1. Sales data on desktop and portable computers (1978–2006).

offering a higher quantity of a particular characteristic. In equilibrium, the marginal cost of producing a characteristic with a particular quantity is equal to the marginal benefit which consumers' receive (Epple, 1987).

Prices (p) of laptops can, therefore, be expressed as a set of ergonomic (E) and technological (T) characteristics:

$$p = f(E,\ T) \tag{1}$$

Rosen (1974) showed that the hedonic regressions identify equilibria intersections between the production possibility frontiers of producers with varying production technologies and the indifference curves of consumers with varying tastes. The hedonic price function is derived by taking the first partial derivative of (1). The partial derivative provides a set of "implicit shadow prices," or "characteristic prices." For an existing set of production possibility curves, the implicit shadow price for a characteristic is the price paid for a marginal improvement in the quantity of one characteristic, holding all other characteristics constant (Griliches, 1971; Pakes, 2003).

The hedonic function is estimated by regression analysis. We consider a differentiated product market in which $i = 1, \ldots, I$ laptops are sold in $t = 1, \ldots, T$ periods. The consumer demand price p_i^t of laptop i in period t is a function of a fixed number (K) characteristics, over which our data provide information on differences in the levels, or quantities, of these characteristics z_{ik}^t. Using data on these variables for the period $t, \ldots, T$, we estimate:

$$p_i^t = \beta_0^t + \sum_{k=1}^{K} \beta_k^t z_{ik}^t + \varepsilon_i^t \tag{2}$$

where ε_i^t is a random error term (independent and identically distributed).

The estimated coefficients β are the shadow prices for each of the K product characteristics, *ceteris paribus*. In our estimated hedonic model, we include ergonomic characteristics in addition to the contribution of technological characteristics.

Saviotti and Metcalfe (1984) extended the hedonic framework to consider the relationship technology and the service characteristics that are valued by consumers (Saviotti, 1985). Firms compete by offering particular combinations of service characteristics they believe will be more attractive to consumers than those of their rivals. These combinations of "service characteristics" are related to a set of "technical characteristics," which are directly related to the underpinning technologies on which the products are based.

Ordinary Least Squares (OLS), based on the mean of all variables, may not be the most appropriate approach to capture trade-offs between particular sets of product characteristics. For this reason, we also estimate a set of quantile models, and conduct further robustness analysis using principle component analysis to establish the strength of the interrelationship between the ergonomic variables, and those technological variables that govern processing power.

There are two methods for estimating hedonic regression models: the time dummy variable model (TVDM) and the adjacent period model. We will use the TVDM model which involves pooling observations for a number of years and including a set of period dummies. The advantage of pooling is that larger number of observations provides greater degrees of freedom. Pooled models are reliable when short periods are considered, and the dimensions of the characteristics space are fixed, i.e., completely new characteristics are not introduced during the period under consideration (Requena-Silvente and Walker, 2006). As discussed above, our data set meets both criteria.

5. Hypotheses

Generally speaking, if firms' designers are effectively tackling a reverse salient in their products, then we expect the interaction term between the characteristics associated with the reverse salient to be statistically significant and that the estimated coefficient of the interaction term to be positive. If this were not the case and, alternatively, the estimated coefficient is negative, then it would indicate ineffective design solutions with designers failing to successfully address the reverse salient within their products. Specifically, in the case of the ergonomic reverse salient, a positive interaction effect between screen size and weight indicates that users value more weight if the increased weight is effectively exploited to provide a larger screen size, that is, to overcome the reverse salient.

Hypothesis 1. A positive characteristics price is paid for the interaction between screen size and weight in laptop products

By similar reasoning, we expect there to be a positive coefficient reflecting effective solutions to the technological reverse salient between microprocessor clock speed, (RAM), and hard disk capacity. An increase in the value of each of these characteristic will be higher if accompanied by a balanced improvement in the other two characteristics. Thus, the two-way interactions as well as the three-way interaction effects are expected to be positive.

Hypothesis 2. A positive characteristics price is paid for the interaction between processing power, RAM and hard disk capacity in laptop products

6. Data and model specification

Our data set is collected from information published in the UK consumer magazine *WhatPC?* This is a well-known, reputable, and publicly available source for secondary data. As a data source, it offers a number of advantages. First, the data are consistent and complete. Second, the use of an independent, publicly available source enables other researchers to access the same information to replicate results. *WhatPC?* was a consumer magazine that produced an annual "Buyers Guide" listing makes, models, recommended retail prices, and features. In total, 746 models are listed in the Buyers Guides between 1993 and 1996, produced by 83 independent, competing manufacturers.

The dependent variable *list_price (1993)* is created to account for inflation. Listed model prices are deflated using the official UK deflator, with 1993 as the base period. The data set contains eight independent ergonomic and technological characteristic variables. The ergonomic characteristics are *screen_area* (length × width of screen) measured in square centimeter; *weight* (the total weight of each laptop) measured in kilograms; and *height* (the height of the base unit) in centimeter. We expect the demand price for *height* to be curvilinear. Higher base units allowed larger disk drive units to be installed, but increased base unit height makes a portable bulky and more difficult to carry, and requires more space or storage. Therefore we include *height* and $height^2$ in the estimated regressions.

Following Chwelos (2003), we use a rich set of characteristics that together affect computing power. These are *clock_speed* (microprocessor speed) measured in megahertz; *memory* (cache speed or RAM) measured in kilobytes; and *harddisk* (hard disk capacity) in megabytes. We expect the demand price for *memory* to be curvilinear. Some firms at this time offered, for an additional upgrade price, with double the RAM. We therefore include *memory* and $memory^2$ in the estimated regressions.

We also have information on graphics cards. At this time some products in the data set came with lower-quality color graphics adaptor (CGA) cards, while others offered higher-quality video graphics adaptor (VGA) cards. This dichotomous variable *vga* takes a value of 1 if a portable is loaded with VGA graphics card or a value of 0 if it has a CGA card.

Consumers were also offered a choice between monochrome displays, which were easier and cheaper to produce, and color displays. *color* is a dichotomous variable which takes a value of 1 if a portable has a color screen or a value of 0 if it has a monochrome screen. One would expect consumers to pay higher prices for higher-quality graphics cards and for color displays. Note that the variables *vga* and *color* are independent of screen size.

Our data set includes two control variables: year and firm names. In hedonic price regressions, time and firm variables are commonly used to control for omitted variables. Time dummies are proxies for omitted market effects. Since Chow (1967), empirical studies of computers generally include year dummies to control for the Moore's law doubling of processing capacity (on circuit boards of a given size and weight) every 18 months (Moore, 1965). As discussed, this will also pick up the effect of miniaturization in disk drives in the period 1993–1996. 1993 is taken as the base year, so estimated coefficients for the dummies *year94*, *year95*, and *year96* are differentials relative to this base year.

Firm name dummies control for unobserved quality and hardware product features that are additional to our core set of ergonomic and technological characteristics. These firm name dummies may additionally pick up brand equity among manufacturers that are able to charge above-average prices for products with the same quality of characteristics as their rivals (see previous studies by Keller, 1993; Ragaswami *et al.*, 1993; Park and Srinivasan, 1994; Berndt and Rappaport, 2001; and Windrum, 2005). There are a total of 83 firm dummies.[5] Peacock is randomly selected as the base firm.

5 The firm dummies are Acer, AJP, Akhter, Ambra, Amstrad, Apricot, Aria, Aries, AST, Atomstyl, Beltron, Carrera, Centerpr, CIC, Colossus, Comcen, Compaq, CompuAdd, Compusys, Copam, DCS, DEC, Dell, Delta, Dimension, Dolch, Dual, Elonex,

We estimate the hedonic model using OLS regression,

$$\begin{aligned} p_i = \; & \beta_0 + \beta_1 screen\_area + \beta_2 weight + \beta_3 screen\_area * weight \\ & + \beta_4 height + \beta_5 height^2 + \beta_6 clockspeed + \beta_7 memory + \beta_8 memory^2 \\ & + \beta_9 harddisk + \beta_{10} clockspeed * memory * harddisk \\ & + \beta_{11} clockspeed * memory + \beta_{12} memory * harddisk \\ & + \beta_{13} clockspeed * harddisk + \beta_{14} colour + \beta_{15} VGA + controls + \epsilon_i \end{aligned} \tag{3}$$

If firms are tackling the ergonomic reverse salient effectively (*H1*), then we expect the interaction term β_3 to be statistically significant and that the estimated price for these solutions is positive.

Similarly, if firms are effectively tackling the technological reverse salient that determines processing power (*H2*), then we expect the three-way interaction term β_{10} and the two-way interaction terms β_{11}, β_{12}, and β_{13}, to be statistically significant and positive.

6.1 Testing for omitted variables

An important concern for any estimated model is misspecification due to omitted variables. There is not a single test for omitted variables. We shall follow current best practice and perform a number of tests on the saved residuals of our estimated models. A well-specified model has a distribution of residuals that is normal (Gaussian). Alternatively, a distribution of residuals that is nonnormal (non-Gaussian) indicates model misspecification. We will inspect the distribution visually the kernel density of the estimated residuals using standardized normal probability and quintile–normal plots.

A second test is the Shapiro–Wilk W test. This is a non-graphical test for normality of the residuals, and is appropriate for sample sizes between 50 and 2000. A median value of $W = 1$ indicates the saved residual samples are normally distributed.

The third test we shall employ is the Ramsey RESET test statistic. This is a test for functional misspecification of the independent variables included in a model. It tests whether higher-order terms of these variables are significant. It cannot pick up the influence of other (omitted) variables.

6.2 Robustness

We conduct two types of robustness check. First, quantile methods are applied to the data. In effect, we rerun the three estimated models for the median priced portable at the 50th percentile of the price distribution. Quantile regression is a semi-parametric method. The conditional quantile has a linear form but does not impose a set of assumptions regarding the conditional distribution, and minimizes the weighted absolute deviations to estimate conditional quantile (percentile) functions (Koenker and Bassett, 1978; Koenker and Hallock, 2001). For the median (50th percentile), symmetric weights are used. By contrast, classical OLS regression minimizes the sums of squared residuals to estimate models for conditional mean functions.

The issue of heteroskedasticity in standard errors is dealt with using Gould's bootstrapping procedure (Gould, 1992; Gould, 1979). Standard errors are obtained via 1000 replications of a panel bootstrap. This is drawn using a fixed initial seed that is 1001, with each individual bootstrapped sample containing the same number of observations as the original sample. The software used in all our estimations is Stata 12.[6]

A second robustness check is to apply principal components analysis (PCA) to examine the underlying structure of interdependencies between variables. The expectation is that strong correlations between the ergonomic characteristics of screen size and total weight on the one hand, and on the other, product characteristics which together govern computing power. PCA is an established procedure for identifying the structure of linear relationships among interrelated variables. The procedure dates back to Ahamad (1967, 1968), and has been previously been applied in research

Ergo, Escom, Evesham, Gateway, Goldstar, Haval, HiGrade, HP, IBM, ICL, IPC, KT, Leo, Librex, Locland, Maple, Mesh, Mitac, MJN, Munn, NCR, NEC, Obodex, Olivetti, Olympia, Omega, Opti, Opus, Pacific, Panasonic, Paragon, Peacock, Redstone, Reeves, Rock, Sanyo, Samsung, Sharp, Sherry, Suntec, Siemens, TA, Tandon, Tandy, TI, Toshiba, Trigem, Triumph, Tulip, Twinhead, Veridata, Viglen, Vortec, Wyse, and Zenith.

6 http://www.stata.com/stata12/.

Table 1. List of variables

Variable	Description
list_price (1993)	Listed model prices. Deflated using the official UK deflator, with 1993 as the base period. Dependent variable
screen_area	Length × width of laptop screen. Measured in square centimeter. Independent ergonomic variable
weight	Total weight of laptop. Measured in kilograms. Independent ergonomic variable
height	Height of the base unit. Measured in centimeter. Independent ergonomic variable
clock_speed	Microprocessor speed. Measured in megahertz. Independent technological variable
memory	Cache speed (or RAM). Measured in kilobytes. Independent technological variable
harddisk	Hard disk capacity. Measured in megabytes. Independent technological variable
color	Dummy variable = 1 if a laptop has a color screen. Variable = 0 if it has a monochrome screen. Independent technological variable
vga	Dummy variable = 1 if a laptop is loaded with VGA graphics card. Variable = 0 if it has a CGA card. Independent technological variable
firm	Firm dummies: Acer, AJP, Akhter, Ambra, Amstrad, Apricot, Aria, Aries, AST, Atomstyl, Beltron, Carrera, Centerpr, CIC, Colossus, Comcen, Compaq, CompuAdd, Compusys, Copam, DCS, DEC, Dell, Delta, Dimension, Dolch, Dual, Elonex, Ergo, Escom, Evesham, Gateway, Goldstar, Haval, HiGrade, HP, IBM, ICL, IPC, KT, Leo, Librex, Locland, Maple, Mesh, Mitac, MJN, Munn, NCR, NEC, Obodex, Olivetti, Olympia, Omega, Opti, Opus, Pacific, Panasonic, Paragon, Peacock, Redstone, Reeves, Rock, Sanyo, Samsung, Sharp, Sherry, Suntec, Siemens, TA, Tandon, Tandy, TI, Toshiba, Trigem, Triumph, Tulip, Twinhead, Veridata, Viglen, Vortec, Wyse, and Zenith. Peacock is the base firm. Control variable
year	Year dummies for 1994, 1995, and 1996. 1993 is the base year. Control variable

on the product characteristics of aeroplanes and helicopters (Saviotti, 1996), cameras (Windrum, 2005), and tanks (Castaldi *et al.*, 2009).

A set of distinct "components" (each comprising a set of interrelated variables) is estimated using the varimax rotation method with Kaiser normalization. Compared to other clustering techniques, such as factor analysis, PCA does not make strong prior assumptions regarding the extent and the structure of interdependencies among the original set of variables (Stevens, 1992). A further advantage is that one has a clear understanding of the number of restrictions that are used to calculate the principal components. PCA assesses the number of composite variables required to achieve a sound representation of the original set of variables. Kaiser and Jolliffe criteria retain components that have, respectively, eigenvalues greater than 1 or 0.7.

7. Results

7.1 Descriptive results

Table 1 provides the overview of the variables and their definitions, and Table 2 provides the estimated partial correlation coefficients for *list price (1993)* and the eight product characteristics, together with descriptive data on the median, mean average, standard deviation, and minimum and maximum values.

The mean average price of £1779.68 (£5924.98 in current prices) is a reminder of just how expensive portable computers were during the mid-1990s. As discussed, these were business machines, almost exclusively business executives and field sales staff. The cheapest listed model is £595.00 (£1980.90 in current prices), while the most expensive is £6300.00 (£20,974.30 in current prices).[7]

The mean screen area (length × height) is 452 cm^2 (which is approximately the area of a 10-inch × 7-inch screen). This is notable, as it just exceeds the minimum ergonomic size standards for a display intended to be viewed between 30 and 60 cm (see above).

The mean weight of laptops in our data set is 3 kg (6.5 lbs), the lightest model being 1 kg (2.2 lbs), and the heaviest 9 kg (20 lbs), highlighting the significant weight of some laptops in the data set.

The partial correlations reported in Table 1 indicate that strong correlations exist between the ergonomic variables. There are positive partial correlations between screen size and weight in Columns 1 and 2,

7 Calculations use the UK consumer price index deflator.

Table 2. Medians, means, standard deviations, minimum, maximum, and partial correlation coefficients

Variable	Median	Mean	Standard deviation	Minimum	Maximum	1	2	3	4	5	6	7	8	9
1. *list_price (1993)*	1544.27	1779.68	878.87	595.00	6300.00	1								
2. *screen_area*	626.90	652.88	135.11	84.56	1489.32	0.17***	1							
3. *weight*	2.90	3.08	1.12	1.00	9.00	−0.08*	0.76***	1						
4. *height*	49.50	53.25	27.07	4.80	355.60	0.13***	0.46***	0.75***	1					
5. *clock_speed*	33.00	43.16	24.14	8.00	133.00	0.03	0.03	0.01	0.09***	1				
6. *memory*	4096.00	4334.11	2015.62	1024.00	20480.00	0.27***	0.09*	0.03	−0.06*	0.21***	1			
7. *harddisk*	120.00	192.35	161.82	1.00	1000.00	0.05	0.05	0.03E-1	−0.09**	0.55***	0.62***	1		
8. *color*	0	0.34		0	1	0.27***	0.03	0.05E-1	−0.08E-1	0.12***	0.11***	0.51***	1	
9. *vga*	1	0.99		0	1	0.04	0.03E-1	0.06*	0.03	0.05	0.10***	0.08***	0.03	1

Note. $N=744$; $^{***}P<0.01$; $^{**}P<0.05$; $^{*}P<0.10$.

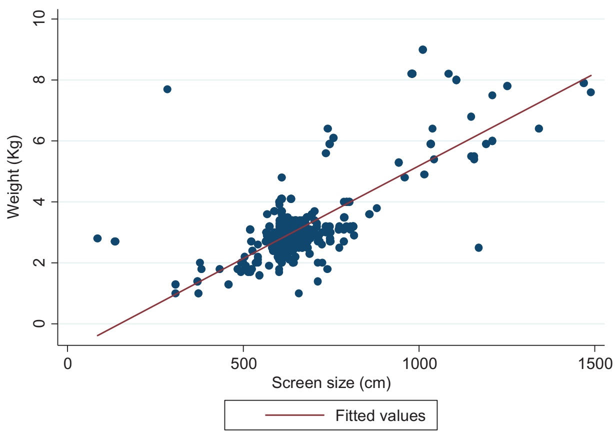

Figure 2. Scatter plot of weight against screen size, with fitted prediction line.

which are statistically significant at the 1% level. Portable computers with larger screen size tend to be heavier in weight due to the larger and more powerful batteries required to support the screen. The scatter plot of Figure 2 indicates a positive correlation between the weight of the portables in the data set and their screen size.

In Columns 5 and 6, we see strong partial correlations between the technology variables which together determine computer processing power. These estimates provide support for *H1* and *H2* of a distinct ergonomic reverse salient and a distinct reverse salient in computing power.

7.2 Estimated OLS models

Table 3 presents information on three estimated (OLS) hedonic price models. BoxCox tests of functional form indicate that the log of list price—*Log_list_price (1993)*—is the correct specification for these models. The log-linear Model 1 does not contain interactions between ergonomic and computing power variables, or firm dummies. Model 2 includes and tests interactions between the ergonomic variables *screen_area* and *weight* (*screen_area*weight)*, and between the computing power variables *clock_speed*, *memory*, and *harddisk* (*clock_speed*memory*harddisk*). Since the latter interaction comprises three variables, a fully specified model also includes pairwise interactions between *clock_speed*memory* and *memory* harddisk*. Model 3 adds the set of firm dummies.

Models 2 and 3 support *H1* that positive shadow prices are paid for designs that tackle the ergonomic reverse salient by addressing the interaction between weight and screen area. The estimated coefficient for *screen_area*weight*

Table 3. Estimated OLS model for consumers' willingness to pay for product characteristics

Variables	Dependent variable: *Log_list_price (1993)*				Base year: 1993		
	Model 1		Model 2		Model 3		
	Coefficient	Robust S.E.	Coefficient	Robust S.E.	Coefficient	Robust S.E.	Standardized coefficient
screen_area	0.00063***	(0.00016)	0.00003	(0.00023)	0.00005	(0.00022)	0.01477
weight	−0.02057	(0.02642)	−0.12375***	(0.04031)	−0.08556**	(0.04201)	−0.21836
height	0.00729***	(0.00198)	0.00542***	(0.00187)	0.00545***	(0.00194)	0.33699
height2	−0.00001**	(0.61e-5)	−0.00001*	(0.536e-5)	−0.00001*	(0.565e-6)	−0.16567
clock_speed	0.00413***	(0.00081)	0.00645	(0.00215)	0.00325*	(0.00194)	0.17913
memory	0.00014***	(0.00002)	0.00011***	(0.00003)	0.00009***	(0.00003)	0.43119
memory2	−5.46e-9***	(0.960e-9)	−6.32e-9***	(0. 791e-9)	−0.727e-8***	(0.854e-9)	−0.45230
harddisk	0.00058***	(0.00013)	0.00026	(0.00071)	0.00013	(0.00025)	0.04744
color	0.31049***	(0.02906)	0.31287***	(0.02803)	0.28605***	(0.02645)	0.30902
vga	0.21079*	(0.11498)	0.26025***	(0.09890)	0.28560***	(0.10874)	0.06293
*screen_area*weight*			0.00013***	(0.00004)	0.00013***	(0.00005)	0.42150
*clock_speed*memory*harddisk*			0.204e-8***	(0.076e-9)	0.201e-8***	(0.656e-9)	0.58919
*clock_speed*memory*			0.783e-6**	(0.468e-6)	0.894e-6**	(0.436e-6)	0.43746
memory harddisk*			0.204e-7***	(0.080e-7)	0.177e-7***	(0.658e-7)	0.59055
*clock_speed*harddisk*			0.205e-4***	(6.81e-6)	0.205e-4***	(6.81e-6)	0.70707
Control variables:							
year94	−0.14305***	(0.03617)	−0.13340***	(0.03281)	−0.13118***	(0.03350)	−0.12440
year95	−0.34256***	(0.03703)	−0.34448***	(0.03388)	−0.33458***	(0.03852)	−0.33475
year96	−0.76013***	(0.05066)	−0.74644***	(0.04836)	−0.72700***	(0.05350)	−0.73217
firm dummies					Yes		
Constant	5.94***	(0.13)	6.34***	(0.18)	6.36***	(0.20)	
AIC	342.30		227.71		215.99		
BIC	402.25		349.74		347.63		
N	744		744		744		
F	64.18		49.32		39.24		
Adjusted R^2	0.63		0.71		0.78		
Residual sum of squares	66.6		64.1		50.9		
Ramsey RESET test	$F(3, 727) = 2.15$ $P > F = 0.09$		$F(3, 722) = 2.21$ $P > F = 0.02$		$F(3, 711) = 2.55$ $P > F = 0.05$		
Shapiro–Wilk test W	0.99511 (P=0.018)		0.99485 (P=0.0131)		0.99579 (P=0.041)		

Note. ***P<0.01; **P<0.05; *P<0.10.

is positive and statistically significant at the 1% level in both models. The estimated standardized coefficient indicates the implicit price for an incremental improvement in this ergonomic interaction.

The inclusion of this interaction variable has a clear impact on the estimated coefficients for the individual variables of *screen_area* and *weight* in Models 2 and 3 (without firm dummies and with firm dummies, respectively). The coefficient for *screen_area* is statistically insignificant in Models 2 and 3, while in Model 1 (which does not include the interaction variable) the estimated coefficient is significant at the 1% level. Also, the size of the estimated coefficient is notably smaller in Models 2 and 3. The lower adjusted R^2 of 0.63 for Model 1, compared to 0.71 and 0.78 for Models 2 and 3, respectively, indicates that the model without this interaction is misspecified.

By contrast, the estimated coefficients for *weight* in Models 2 and 3 are statistically significant (at the 5% level), while in Model 1 the coefficient was not significant at $P < 0.10$. These findings indicate that simpler models, which

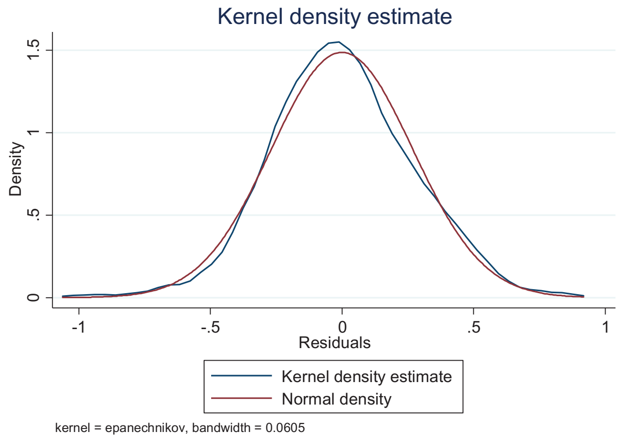

Figure 3. Kernel density estimate of saved residuals for Model 3.

omit this interaction, are misspecified and are misleading with regard to the underlying relationship between prices, screen size, and weight.

In Models 2 and 3, the estimated coefficient of *clock_speed*memory*harddisk* is positive and statistically significant at the 1% level. In addition, the two-way interaction effects for *clock_speed*memory*, *memory* harddisk*, and *clock_speed*harddisk* are also positive and significant, further confirming the reverse salient hypothesis regarding speed, RAM, and hard disk capacity. This supports *H2* that positive shadow prices are paid for the interaction between these variables, which governs computing power.

Finally, we note that the coefficients for the control variables—year dummies and firm name dummies—are significant in Models 2 and 3, respectively, and have the expected positive sign. Laptops with color screens are significantly more expensive than those with monochrome screens, while the same holds true for laptops with VGA graphics card instead of a CGA card.

7.3 Testing for omitted variables

As discussed, there is not a single test for omitted variables and so, following current best practice, we perform a number of tests on the saved residuals of the estimated models to establish whether these are normally distributed. Due to space constraints we report here tests on the saved residuals of Model 3, as this model includes the hypothesized interactions between ergonomic variables and between computing power variables.

Figure 3 is a kernel density graph of the estimated residuals of Model 3. A normal distribution is superimposed on the kernel density graph. The graph indicates that the residuals are normally distributed.

Figure 4 presents standardized normal probability (pnorm) plot and a quintile–normal (qnorm) plot of the saved Model 3 residuals. The standardized normal probability plot is more sensitive to deviances near the mean of the distribution. The standardized normal probability plot for these residuals is ruler flat.

Quintile–normal plots quintiles of residuals vs. quintiles of a normal distribution, and is more sensitive to deviances from normality in the tails of the distribution. Figure 5 indicates three data points as outliers (bottom left-hand corner). Otherwise, the tails are close to normal.

The second test for model misspecification we apply is the Shapiro–Wilk W test. This is a non-graphical test for normality, with a median value of $W = 1$ indicating the saved residual samples are normally distributed. Table 3 reports the Shapiro–Wilk W statistic for each of our estimated models. The critical *P*-values are indicated along with the estimated *W*. The estimated $W = 0.99579$ ($P = 0.041$) for the saved residuals of Model 3. We cannot reject *H0* (at $P = 0.05$ level) that these residuals are normally distributed.

The third test we apply is Ramsey RESET test functional misspecification of the independent variables included in a model. For Model 3, the estimated *F* statistic $= 2.55$ ($P = 0.05$) indicating that further powers of these independent variables do not jointly add further explanatory power to this model.

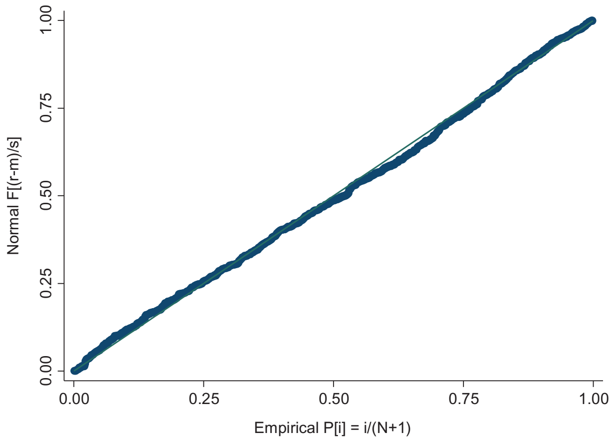

Figure 4. Standardized normal probability plot of Model 3 residuals.

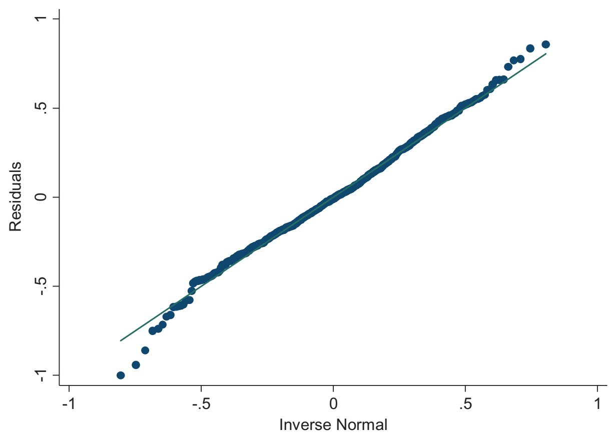

Figure 5. Quintile–normal plot of Model 3 residuals.

7.4 Robustness

The first of our robustness tests is to apply quantile estimation to this set of models. The findings for the median portable (50th percentile) in the price distribution are reported in Table 4 below. As with the estimated OLS models, the inclusion of the interaction variable *screen_area*weight* is statistically significant in Model 5 (without firm dummies) and Model 6 (with firm dummies). When the interaction term is included, the coefficient for *screen_area* is not statistically significant in these models. By contrast, the coefficient is significant, in Model 4, when the interaction terms are omitted. These findings indicate that consumers pay a shadow price for designs that tackle the ergonomic reverse salient, and that models which omit this are misspecified.

We next turn to the principle components analysis (PCA) of the set of product characteristic variables in Table 5. The PCA on these data identifies three distinct components that are orthogonal to one another. The first estimated component is the set of product characteristics that comprise the computing power reverse salient: *clock_speed*, *memory*, and *harddisk*. This component accounts for 36% of the variance across the independent variables. The highest value in this component is *harddisk* (0.910), followed by *clock_speed* (0.878) and *memory* (0.831).

The second estimated component comprises the interrelated ergonomic product characteristics *screen_area* and *weight*, and base unit *height*. This accounts for 27% of variance across all variables.

This further supports the proposition that strong interactions exist between the characteristics screen size and weight that together comprise the ergonomic reverse salient, and are distinct to other product laptop characteristics.

Table 4. Estimated quantile models for consumers' willingness to pay for product characteristics

Variables	Model 4		Model 5		Model 6	
	50th percentile		50th percentile		50th percentile	
	Price: £1542.45		Price: £1542.45		Price: £1542.45	
	Coefficient	Robust S.E.	Coefficient	Robust S.E.	Coefficient	Robust S.E.
screen_area	0.00064***	(0.00020)	0.00004	(0.00032)	0.00001	(0.00030)
weight	−0.00799	(0.03865)	−0.11973*	(0.06390)	0.09653	(0.06406)
height	0.00771**	(0.00373)	0.00384	(0.00305)	0.00400	(0.00373)
height2	−0.00001	(0.00001)	−6.66e-6	(0.00001)	−0.699e-5	(0.00001)
clock_speed	0.00330***	(0.00084)	0.00010	(0. 00004)	0.00532	(0.00337)
memory	0.00015***	(0.00002)	0.14e-3***	(0.23e-4)	0.15e-3***	(0.33e-4)
memory2	−5.80e-9	(2.05e-9)	−0.757e-8	(0.544e-8)	−0.635e-8	(0.411e-8)
Harddisk	0.00066***	(0.00022)	0.00199*	0.00108	0.00184*	(0.00089)
color	0.30495***	(0.03840)	0.31421***	(0.03435)	0.30873***	(0.03322)
vga	0.14064	(0.17674)	0.35329**	(0.17081)	0.27477*	(0.15420)
*screen_area*weight*			0.00016***	(0.00005)	0.00015***	(0.00006)
*clock_speed*memory*harddisk*			0.903e-9***	(0.227e-9)	0.157e-8***	(0.194e-9)
*clock_speed*memory*			0.109e-5	(0.864e-6)	0.605e-6	(0.748e-6)
memory harddisk*			0.405e-6***	(0.194e-6)	0.962e-6***	(0.163e-6)
*clock_speed*harddisk*			0.000023***	(0.00001)	0.00002**	(0.00001)
Control variables:						
year94	−0.19464***	(0.04467)	−0.20217***	(0.04341)	−0.17171***	(0.03977)
year95	−0.39004***	(0.05284)	−0.41718***	(0.06311)	−0.41182***	(0.04842)
year96	−0.85007***	(0.06454)	−0.86977***	(0.09025)	−0.81846***	(0.06513)
firm dummies					Yes	
Constant	5.88***	(0.20)	6.39***	(0.29)	6.26***	(0.26)
N	744		744		744	
Pseudo R^2	0.62		0.68		0.70	
Minimum sum deviations	88.7		80.9		77.8	

The third estimated component comprises the characteristic variables *color* (0.698) and *vga* (0.991). These two variables facilitate the rendition of high-quality color images. This estimated component for 12% of variance across all variables.

The estimated correlation matrix on which the PCA is constructed is within the critical 1% level. The estimated Kaiser–Meyer–Olkin statistic of sampling adequacy is 0.638, well above the critical 0.5 level.

8. Discussion and conclusions

Our research findings highlight the need for a deeper understanding, and analysis, of the contributions of ergonomic design to product innovation. Studies that omit these contributions, i.e., focus solely on technologically driven functional performance, significantly under-report innovation. We have shown that the design trajectory in portable computers was strongly shaped by the ergonomic trade-off that exists between screen quality and total weight. Over the course of time, portable computer designers have sought to improve usability by developing products with larger screens, while simultaneously addressing the problem of increased weight as this negatively affects portability.

Our empirical analysis has applied hedonic price methods for studying trade-offs in product characteristics: however, we have extended the analysis to include the key ergonomic variables "screen size" and "weight" in addition to key technology variables. These results indicate that designers have separately addressed the ergonomic reverse salient and the technological issue of computer power when engaging in product innovation. Importantly, the findings indicate that consumers positively value the solutions to the ergonomic reverse salient that rival firms offer up to the market.

Table 5. Principal components for independent product characteristics

Variables	Retained principal components		
	Computing power reverse salient	Ergonomic reverse salient	Color
screen_area	−0.086	0.796	0.052
weight	−0.035	0.967	0.025
height	−0.006	0.819	−0.039
clock_speed	0.878	−0.066	0.066
memory	0.831	−0.079	0.115
harddisk	0.910	−0.002	0.029
color	−0.028	−0.016	0.698
vga	0.090	0.029	0.991
Number of observations	746	746	746
Eigenvalues:			
Total	2.909	2.173	0.969
% of Variance	36.357	27.164	12.110
Cumulative % of variance	36.357	63.521	75.630

Note. Kaiser–Meyer–Olkin measure of sampling adequacy 0.638.
Bartlett's test of sphericity: approximate χ^2 2904.811.
DF: 28.
Significance: 0.000.
Rotation method: varimax with Kaiser normalization.
Rotation converged in four iterations.

The current research has a number of limitations. First, ours is a detailed study of an ergonomic reverse salient in one particular product class: studies of ergonomic reverse salients in other product classes are required to establish the generalizability of our findings. Second, our empirical frame has sought to minimize well-known problems associated with omitted variables in cross-sectional studies. Great care was taken to select a period for data collection: in the period 1993–1996, the laptop computer was a stand-alone business product (i.e., pre-Internet), using a limited set of business software that was highly standardized. The set of product characteristics found in the portables at this time was also limited, certainly in comparison with later periods. Firm dummies capture brand effects and additional, idiosyncratic product features offered by firms.

It is hoped that the research presented in this article will stimulate further research on ergonomic design, and the effective management of ergonomic, aesthetic, and technological inputs to innovation. There is a clear need for further research into ergonomics, and the role played by ergonomic reverse salients in shaping the innovation trajectory of other product classes. Developing a set of stylized facts about the role of ergonomics not only requires a retesting of the hypotheses advanced in this article but also the development of new research questions. For example, it is important to know whether the significance of ergonomic features, relative to technology and aesthetics, varies over the product lifecycle, and if so, what factors explain this. The demands on data collection, and problems of omitted variable bias, for longitudinal studies such as this are demanding but potentially highly rewarding.

The analysis presented in this article has focused on design ergonomics. This is driven by a need to redress an imbalance in recent scholarship in design (Stoneman, 2010; Eisenman, 2013), which has expanded our understanding of the role of aesthetics in innovation but paid little or no attention to the role of ergonomics. These two areas of design are not exclusive. While aesthetics does not play a key role in the development of portable computers during the era studied, an important future avenue for research is the development of case studies in which both ergonomic and aesthetic design, along with technology, are analyzed as shaping factors in the innovation process.

Finally, our empirical findings hold important implications for managers. Successful product management requires an understanding of the role(s) of design within innovation, and how the inputs of designers complement the technological inputs of R&D. Designers have much to offer in determining market positioning, understanding and creating demand, and in addressing and unlocking the latent needs of consumers. As Moody (1980) has stated, managers must address the opposition of R&D engineers to industrial designers. Long-term competitiveness requires the strategic harnessing and integration of inputs from both designers and R&D engineers. Successful companies focus their product innovation activities along well-defined design trajectories that carry a company's recognizable signature.

Product design is expected to become increasingly decisive for a company's competitive advantage. For example, figures from the UK Design Council (2010) indicate a 15% growth in real earnings over the period 2005–2010, despite that country's economic downturn in 2008 and recession in 2009. This represents a major shift in the management of product innovation, which in many sectors has been the preserve of the R&D department. Understanding this shift and developing new ways to create value are important challenges for both managers and academic scholars of innovation.

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